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Improving climate projections using “intelligent” ensembles

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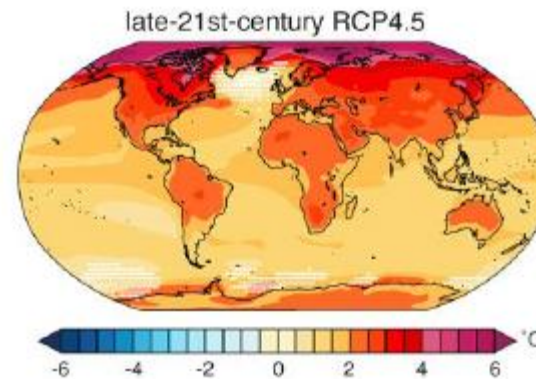
Presented at the AGU Joint Assembly in Montréal, Canada
May 5, 2015

CMIP5: group of ~45 models

CMIP5 Model

BCC-CSM1.1
BCC-CSM1.1.m
BNU-ESM
CanCM4
CanESM2
CCSM4
CESM1-BGC
CESM1-CAM5
CESM1-WACCM
CMCC-CESM
CMCC-CM
CMCC-CMS
CNRM-CM5
ACCESS1.0
ACCESS1.3
CSIRO-Mk3.6.0
EC-EARTH
FGOALS-g2
FGOALS-s2
FIO-ESM
GFDL-CM3
GFDL-ESM2G
GFDL-ESM2M
GISS-E2-H
GISS-E2-H-CC
GISS-E2-R
GISS-E2-R-CC
HadCM3
HadGEM2-AO
HadGEM2-CC
HadGEM2-ES
INM-CM4
IPSL-CM5A-LR
IPSL-CM5A-MR
IPSL-CM5B-LR
MIROC4h
MIROC5
MIROC-ESM
MIROC-ESM-CHEM
MPI-ESM-LR
MPI-ESM-MR
MPI-ESM-P
MRI-CGCM3
NorESM1-M
NorESM1-ME

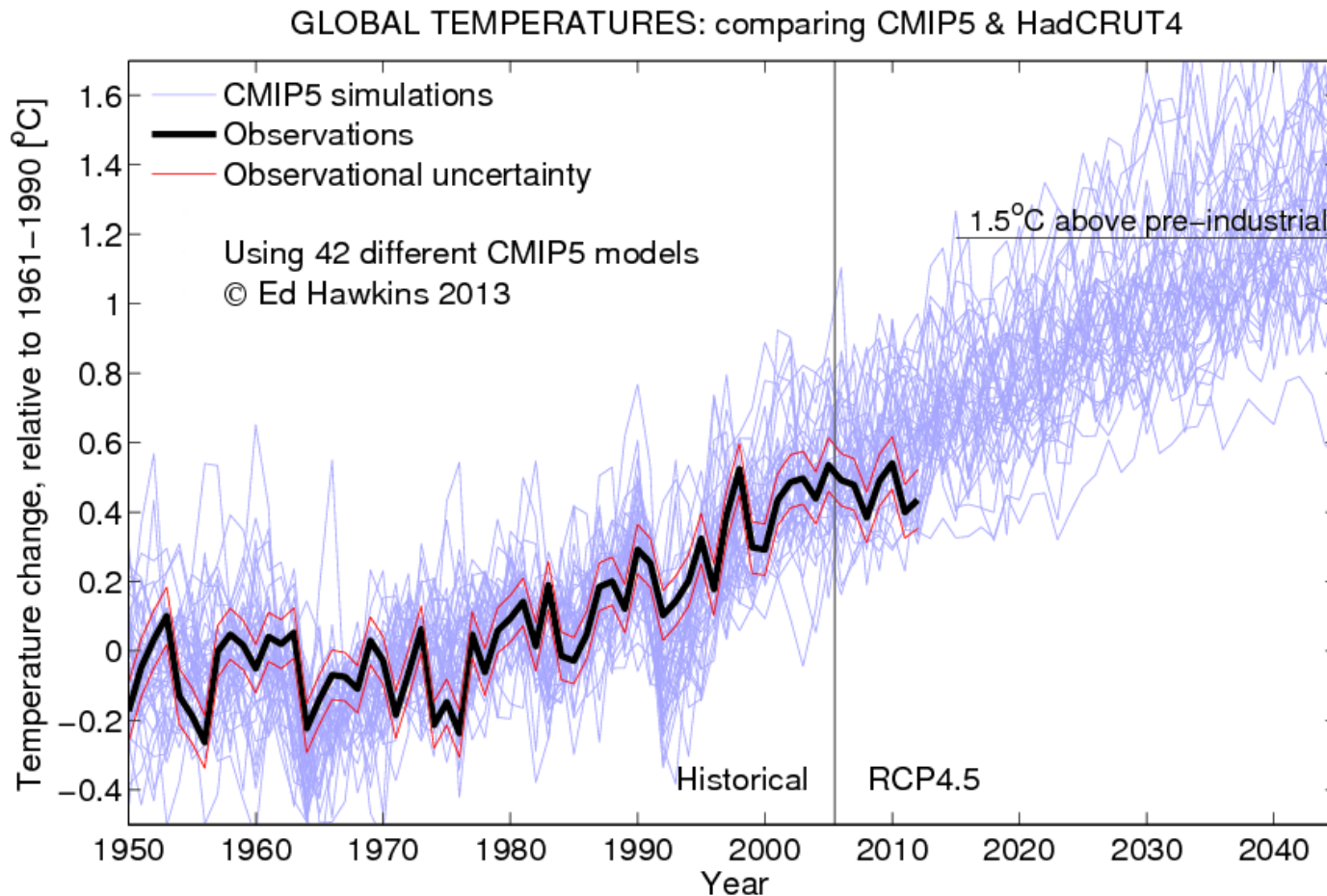
Models are averaged together to make
climate predictions



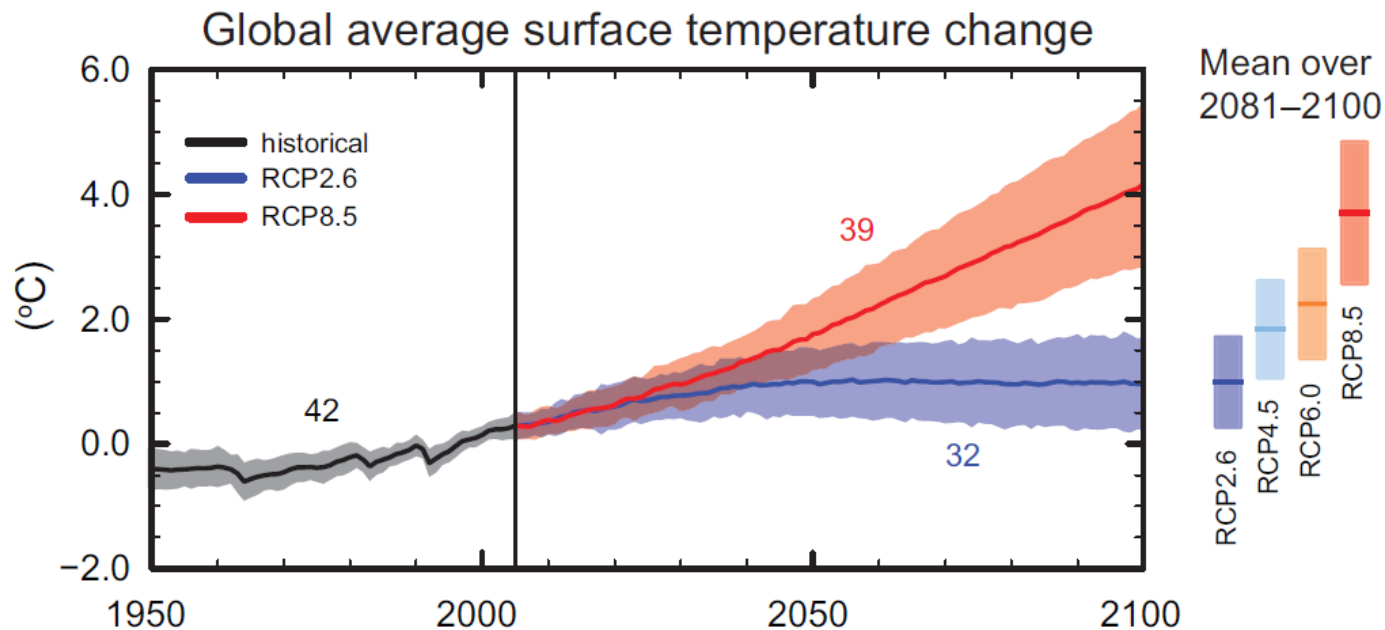
Predicted temperature changes

IPCC AR5 Ch.12

But models can have a large spread in predictions,
and individual models can perform
very differently from observations



The traditional **Multi-Model Ensemble Approach** uses the model mean to provide an improved “best estimate” forecast

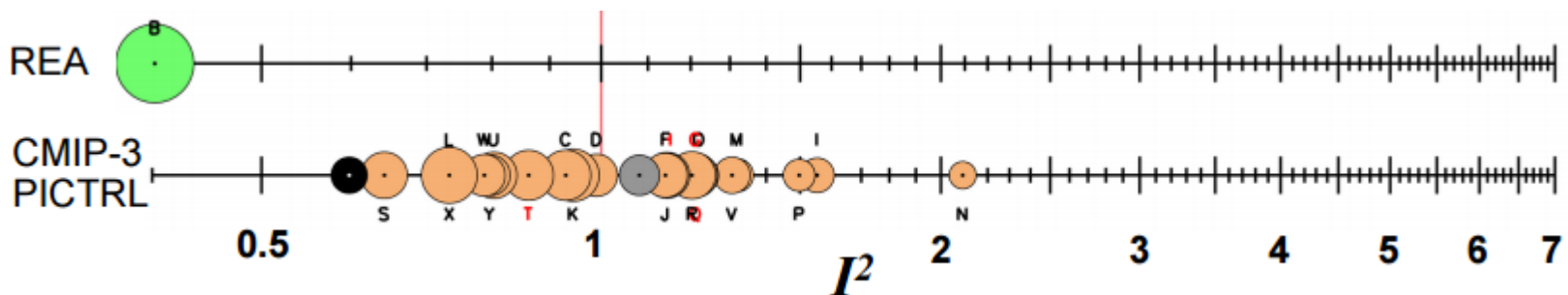


IPCC AR5 Figure SPM.7

The multi-model ensemble generally performs better than individual models

Example: I^2 performance index (Reichler and Kim 2008)

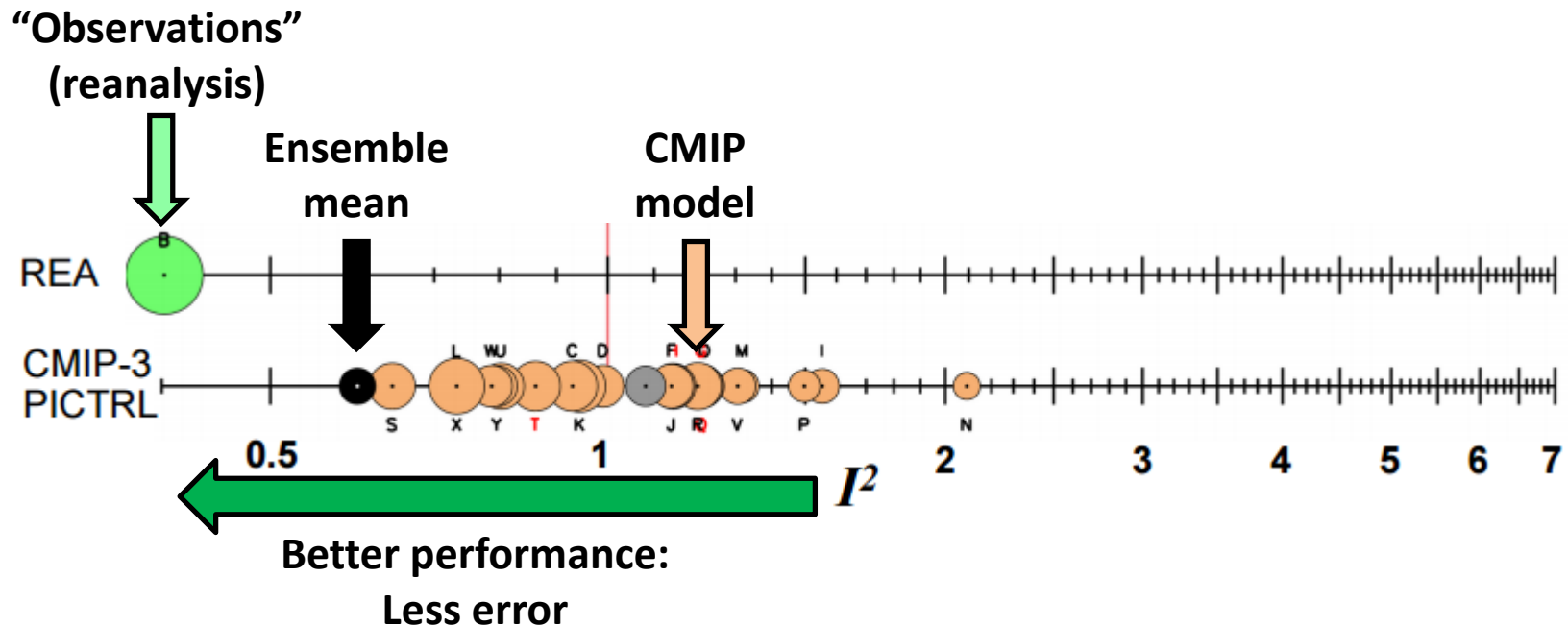
Calculates aggregated model errors relative to NCEP/NCAR reanalyses for multiple climate variables



The multi-model ensemble generally performs better than individual models

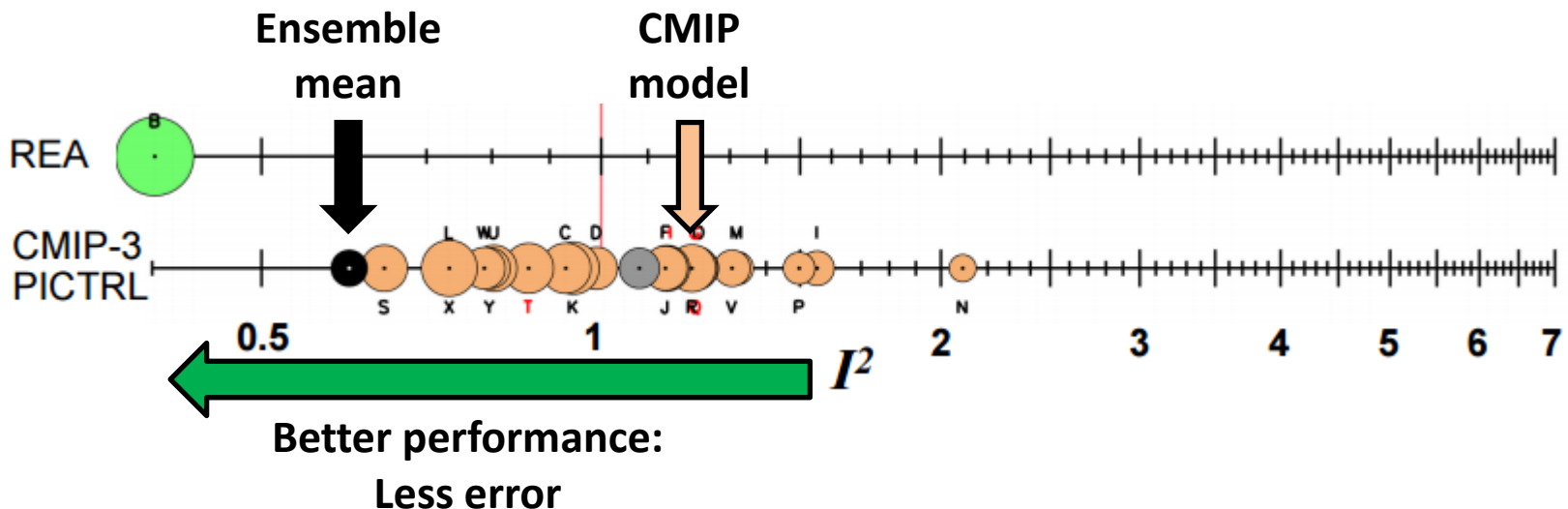
Example: I^2 performance index (Reichler and Kim 2008)

Calculates aggregated model errors relative to NCEP/NCAR reanalyses for multiple climate variables

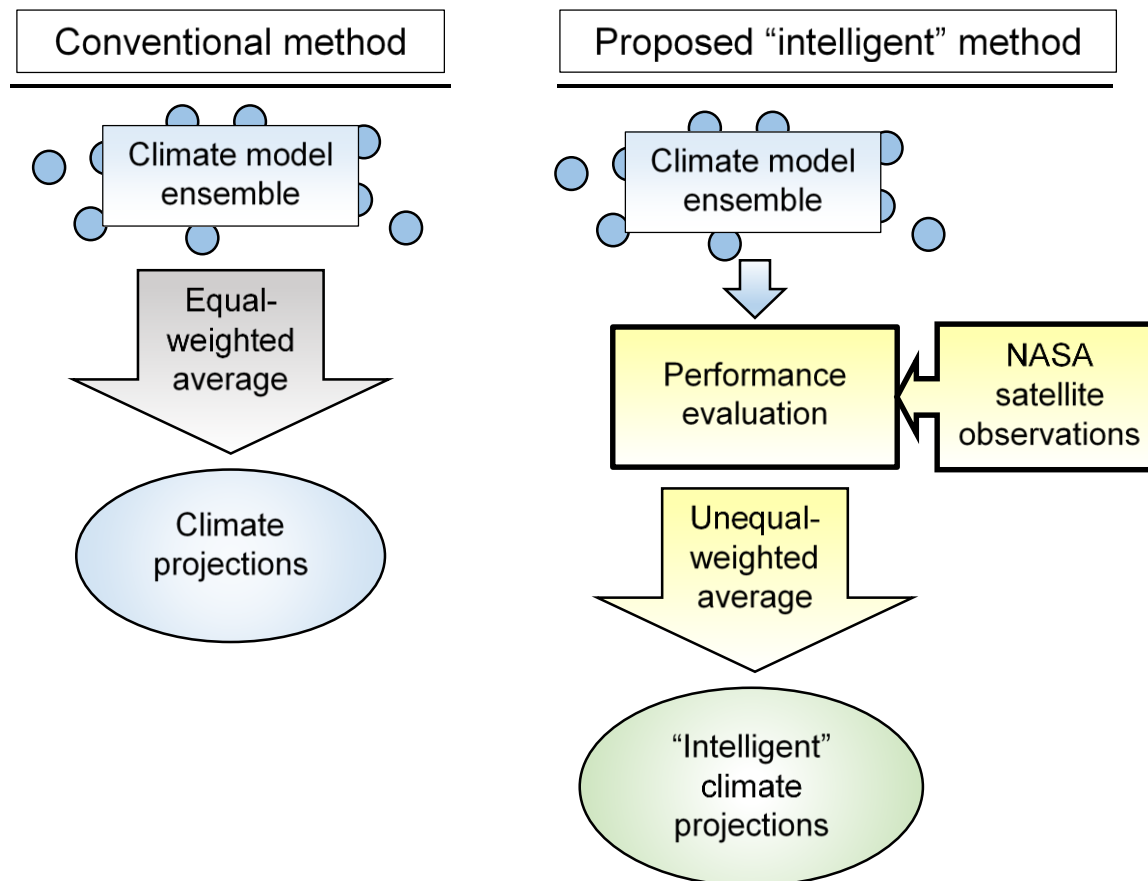


Some models perform better than others:

Can we use knowledge of model performance for a better way to combine model output?



The “intelligent ensemble” approach for creating multi-model ensemble projections



Project goal:
determine future climate state
using observed current climate
and an ensemble of models

$$f(x_{obs}) = \Delta x$$

Observed
climate

Future
climate
state

Previous work has explored model performance and some unequal-weighting metrics

Several examples:

- Use only subsets of models (USGCRP 2009)
- Create mean-state metrics using model skill (Giorgi and Mearns 2002, 2003; Reichler and Kim 2008)
- Constrain model projections using mean-state CERES data (Tett et al. 2013)
- Weight using regression between observed and future trends (Boe et al 2009)
- Apply bias correction for present-day to future trends (Baker and Huang 2012)

“The community would benefit from a larger set of proposed methods and metrics” (Knutti 2010)

This project tests new climate model performance metrics

Radiation budget quantities:

- Top-of-atmosphere (TOA) longwave (LW) and shortwave (SW) radiation fluxes
- Surface LW and SW radiation fluxes
- Surface temperature

New process-oriented metrics:

- $\frac{\Delta TOA \text{ Radiation flux}}{\Delta \text{Surface temperature}}$

Statistical tests:

- F-test for equal variances
- Kolmogorov-Smirnov test for distribution similarity
- Earth Mover's Distance (EMD): test for area of distribution overlap
- Local Variance: test variance of first difference time series (Baker and Taylor 2015)

Model data:

35 CMIP5 models

<http://pcmdi9.llnl.gov/>

- ‘Pre-Industrial Control’ simulations (monthly mean, 100 years) to create metric weights
- ‘RCP 8.5’ future simulations (monthly mean, 2081-2100 minus 2011-2030 to produce 21st-century trends)

Observational datasets:

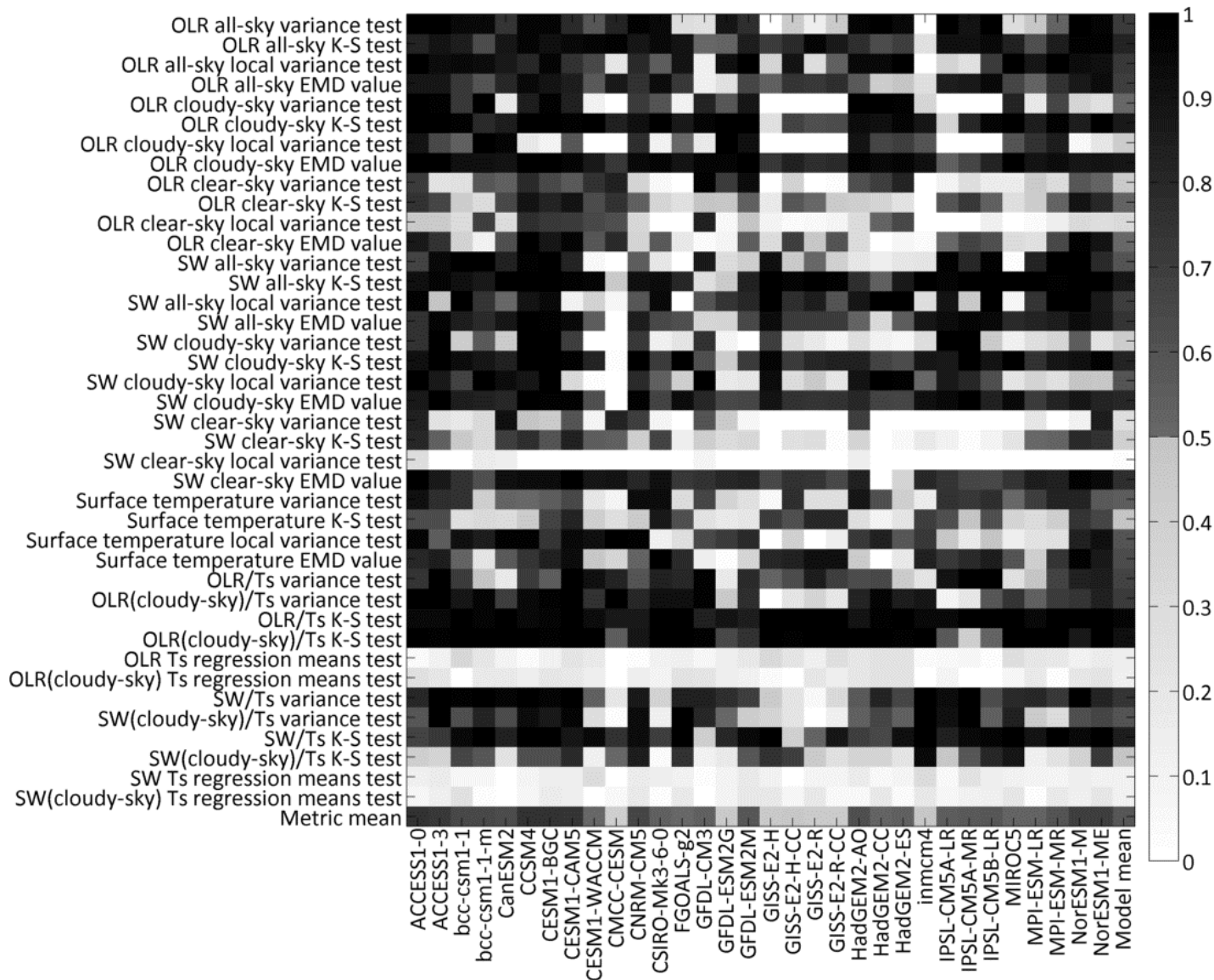
NASA CERES EBAF-TOA and surface monthly global-mean

<http://ceres.larc.nasa.gov/>

NASA GISS Surface Temperature Analysis (GISTEMP)

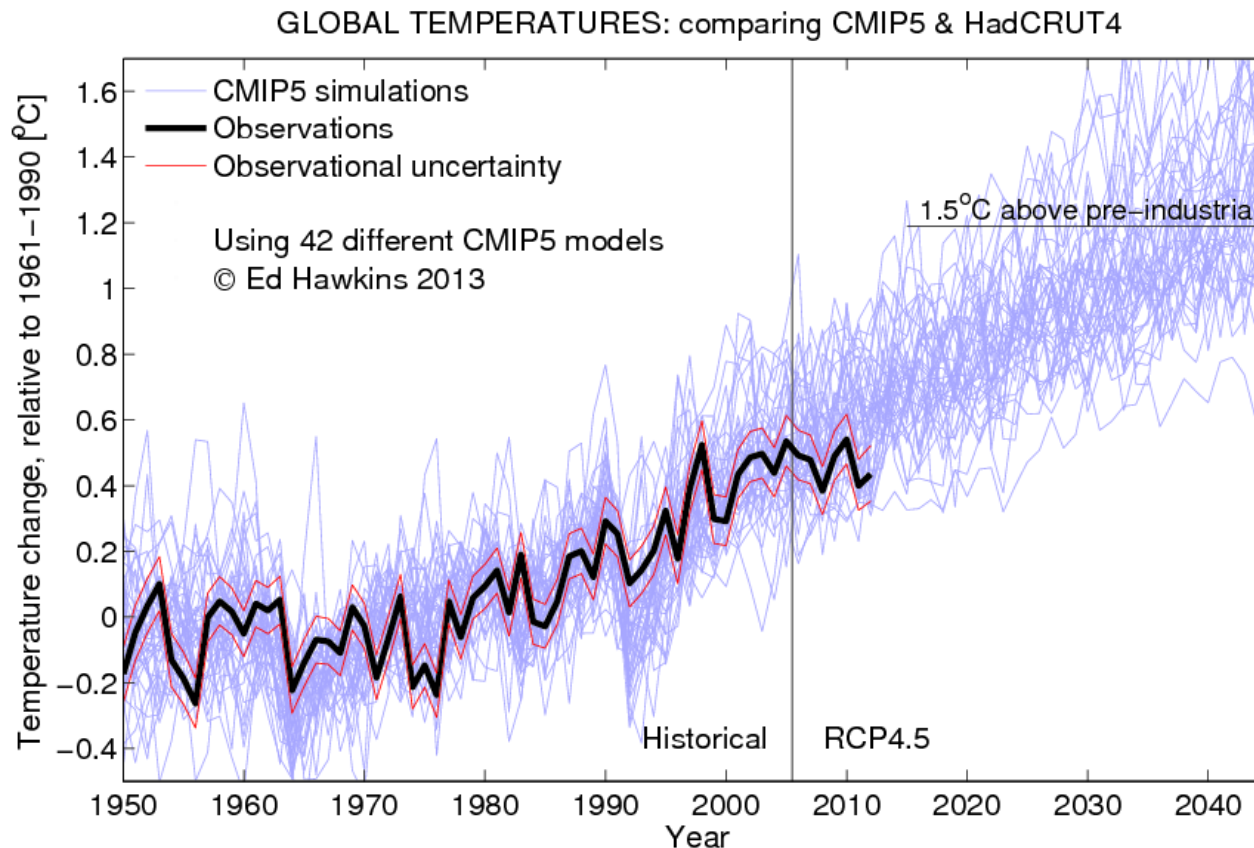
<http://data.giss.nasa.gov/gistemp/>

Step 1: Test model quality with selected metrics

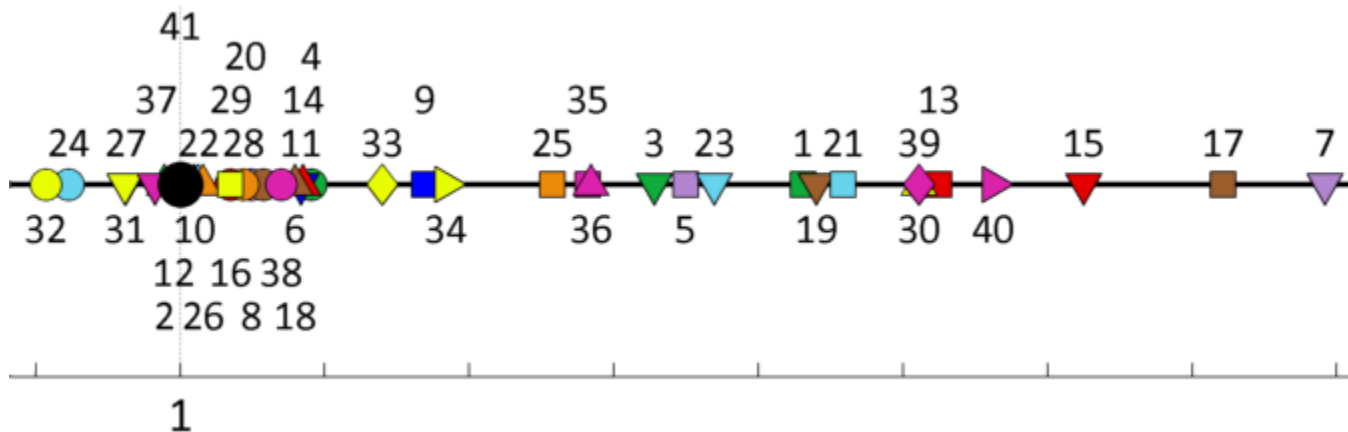


Step 2: Using skill-subset of models, apply “perfect model” approach (Räisänen and Palmer 2001)

Create set of potential “Earths” each with a continuous time series of observations

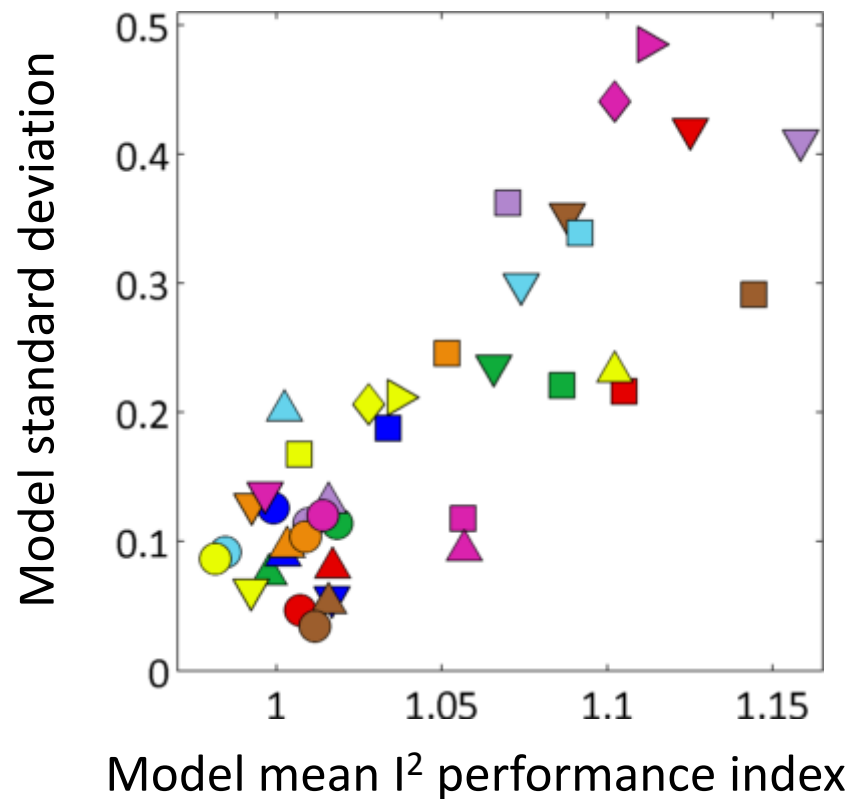


- | | | |
|--|--|---|
| ■ 1 OLR all-sky variance test | ■ 17 SW cloudy-sky variance test | ◆ 33 OLR Ts regression means test |
| ▲ 2 OLR all-sky K-S test | ▲ 18 SW cloudy-sky K-S test | ▶ 34 OLR(cloudy-sky) Ts regression means test |
| ▼ 3 OLR all-sky local variance test | ▼ 19 SW cloudy-sky local variance test | ■ 35 SW/Ts variance test |
| ● 4 OLR all-sky EMD value | ● 20 SW cloudy-sky EMD value | ▲ 36 SW(cloudy-sky)/Ts variance test |
| ■ 5 OLR cloudy-sky variance test | ■ 21 SW clear-sky variance test | ▼ 37 SW/Ts K-S test |
| ▲ 6 OLR cloudy-sky K-S test | ▲ 22 SW clear-sky K-S test | ● 38 SW(cloudy-sky)/Ts K-S test |
| ▼ 7 OLR cloudy-sky local variance test | ▼ 23 SW clear-sky local variance test | ◆ 39 SW Ts regression means test |
| ● 8 OLR cloudy-sky EMD value | ● 24 SW clear-sky EMD value | ▶ 40 SW(cloudy-sky) Ts regression means test |
| ■ 9 OLR clear-sky variance test | ■ 25 Surface temperature variance test | ● 41 Equal-weighted mean |
| ▲ 10 OLR clear-sky K-S test | ▲ 26 Surface temperature K-S test | |
| ▼ 11 OLR clear-sky local variance test | ▼ 27 Surface temperature local variance test | |
| ● 12 OLR clear-sky EMD value | ● 28 Surface temperature EMD value | |
| ■ 13 SW all-sky variance test | ■ 29 OLR/Ts variance test | |
| ▲ 14 SW all-sky K-S test | ▲ 30 OLR(cloudy-sky)/Ts variance test | |
| ▼ 15 SW all-sky local variance test | ▼ 31 OLR/Ts K-S test | |
| ● 16 SW all-sky EMD value | ● 32 OLR(cloudy-sky)/Ts K-S test | |

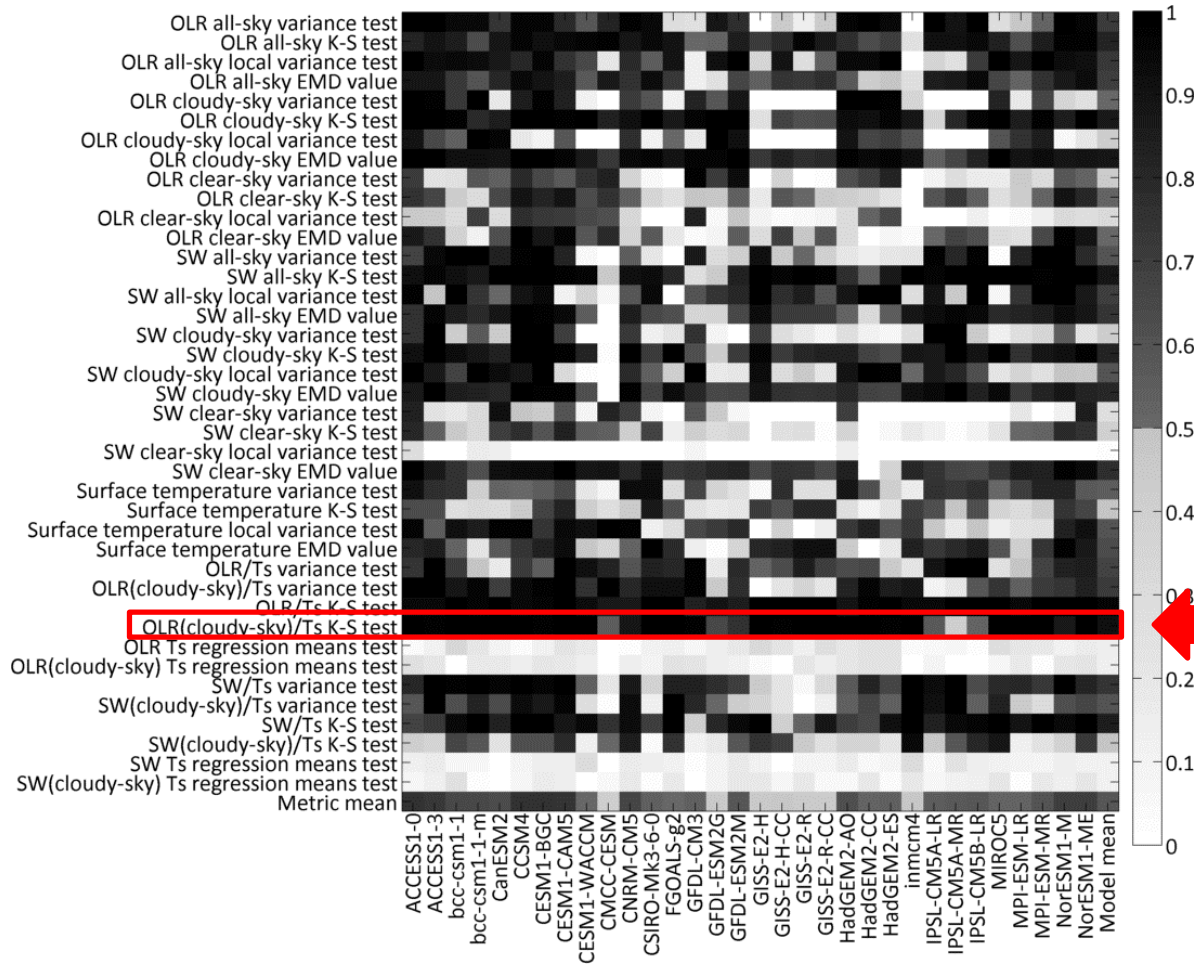


Metric performance and consistency is correlated:

Metrics which best reduce error in future projections
behave similarly across model ensemble



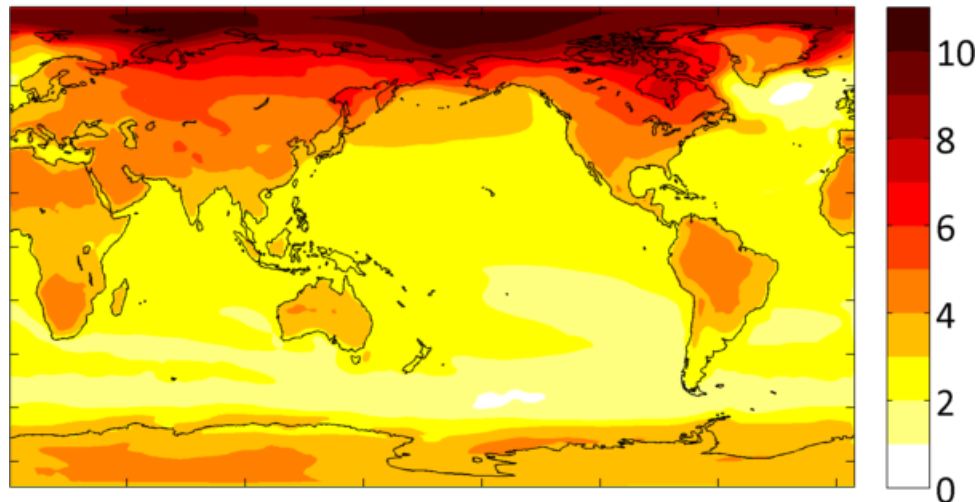
Step 3: Using best-performing metrics, create new “intelligent ensemble” projections



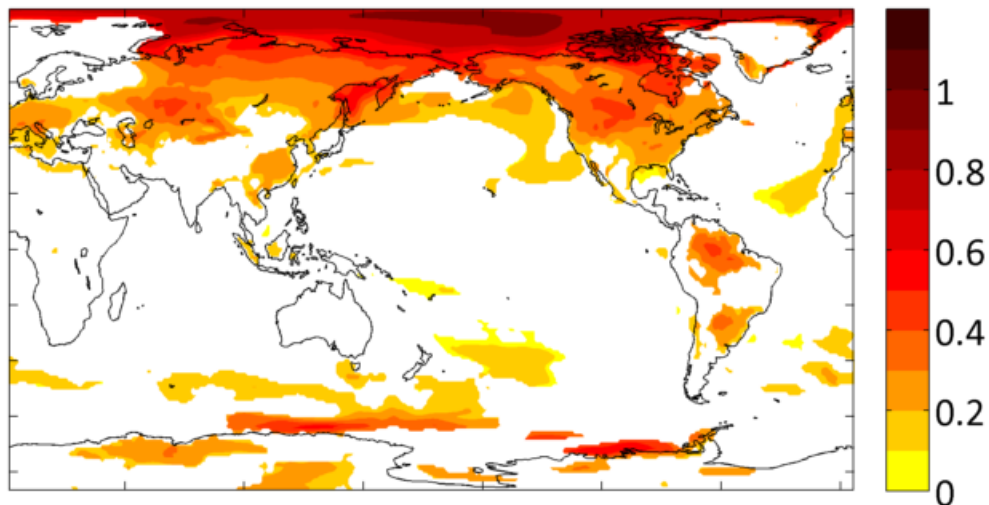
Use metric values
as model weights
to create unequal-
weighted mean
projections

Results: new 21st-century projections (surface temperature)

"Intelligent" ensemble mean temperature trend ($^{\circ}\text{C}$)

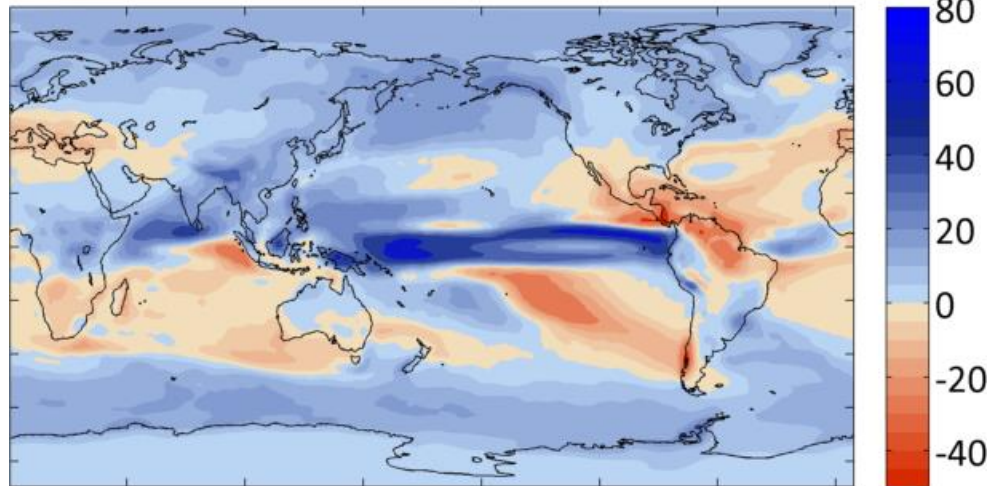


Difference between "Intelligent" and Equal-weight ensemble means ($^{\circ}\text{C}$)

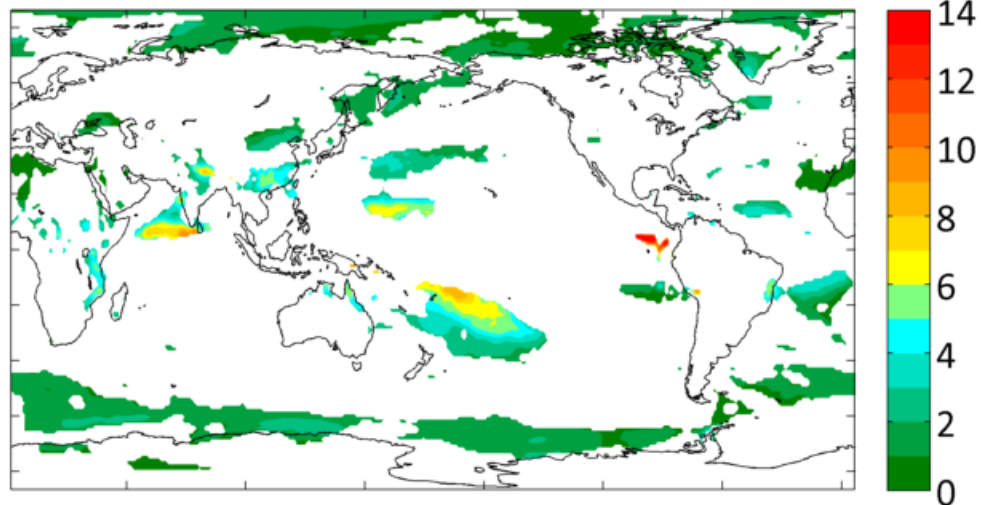


Results: new 21st-century projections (precipitation)

"Intelligent" ensemble mean precipitation trend (cm/year)

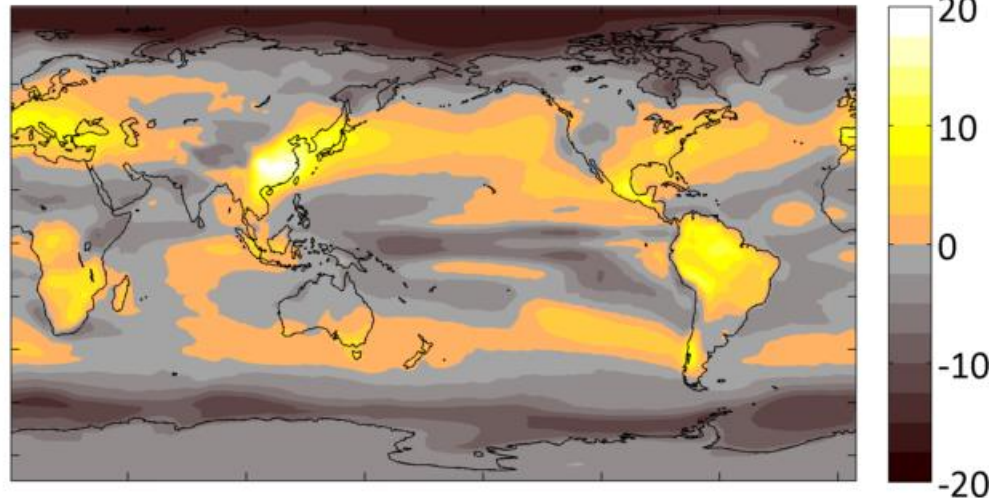


Difference between "Intelligent" and Equal-weight ensemble means (cm/year)

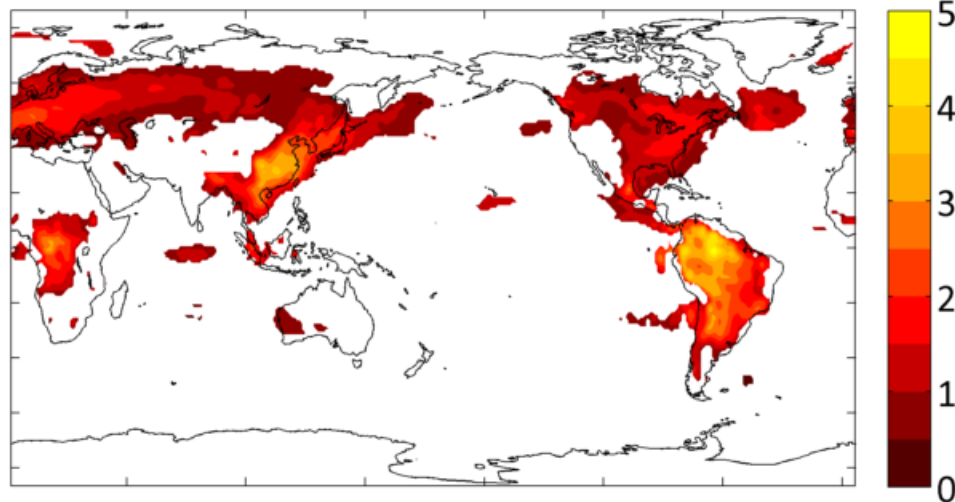


Results: new 21st-century projections (surface downward SW radiation)

"Intelligent" ensemble mean surface shortwave radiation trend (W/m^2)

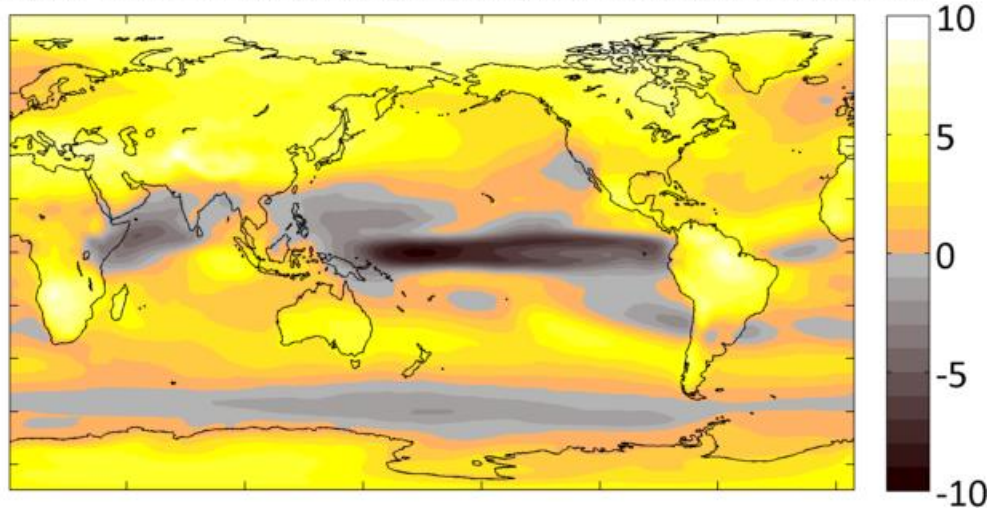


Difference between "Intelligent" and Equal-weight ensemble means (W/m^2)

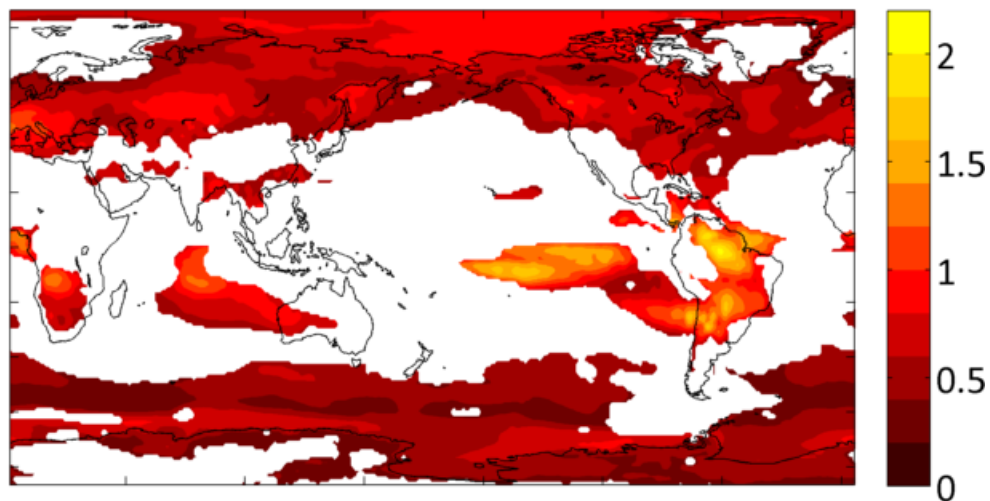


Results: new 21st-century projections (TOA LW radiation)

"Intelligent" ensemble mean outgoing longwave radiation trend (W/m^2)

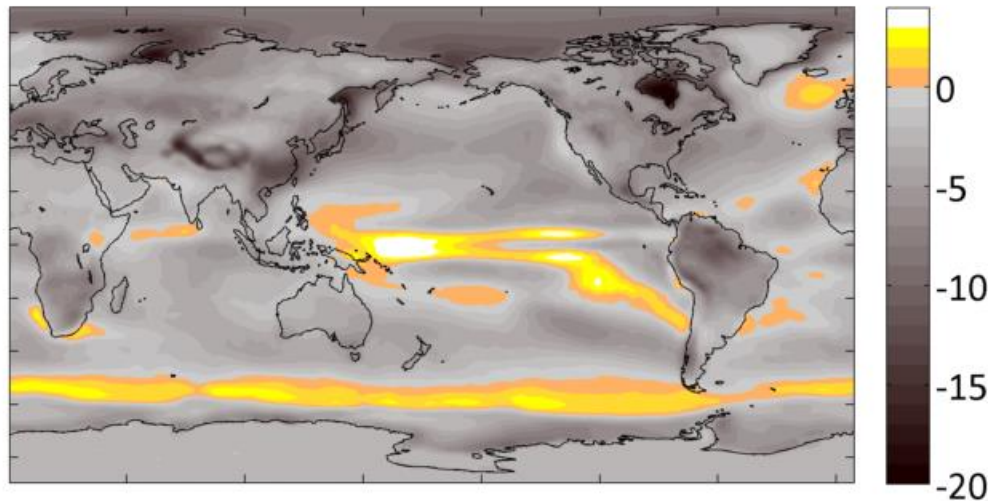


Difference between "Intelligent" and Equal-weight ensemble means (W/m^2)

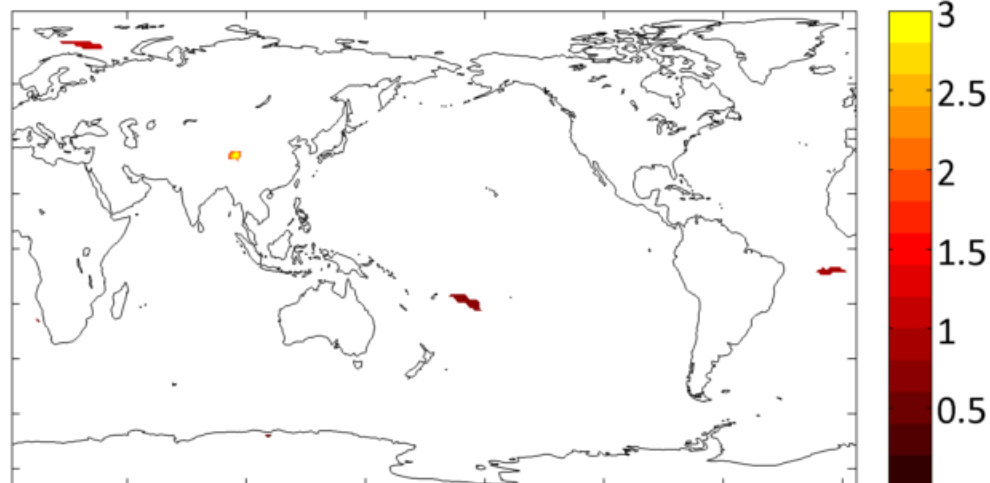


Results: new 21st-century projections (TOA SW radiation)

"Intelligent" ensemble mean reflected shortwave radiation trend (W/m^2)

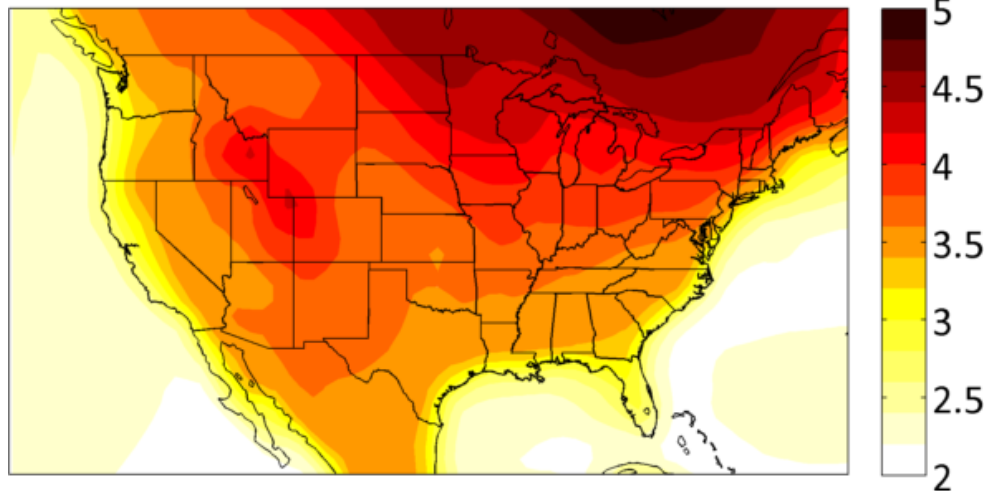


Difference between "Intelligent" and Equal-weight ensemble means (W/m^2)

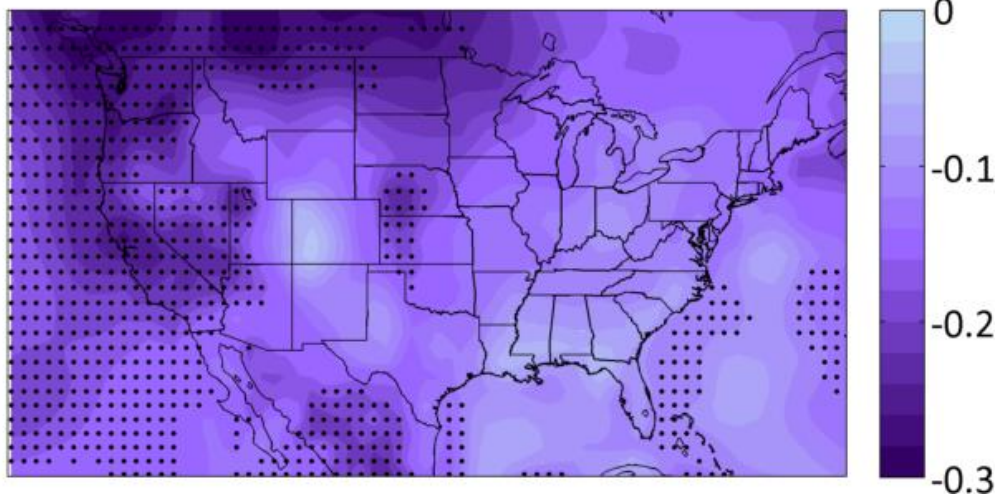


Results: new 21st-century projections (regional-mean weights)

"Intelligent" ensemble mean temperature trend ($^{\circ}\text{C}$)

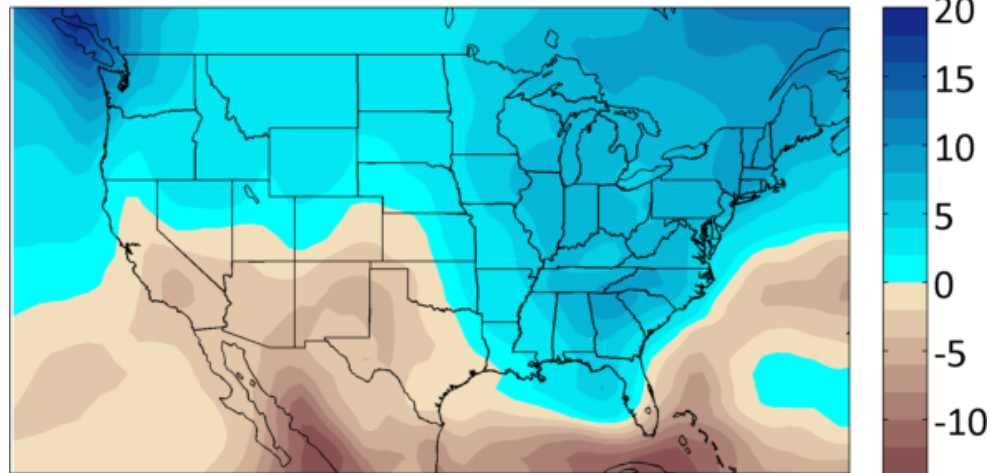


Difference between "Intelligent" and Equal-weight ensemble means ($^{\circ}\text{C}$)

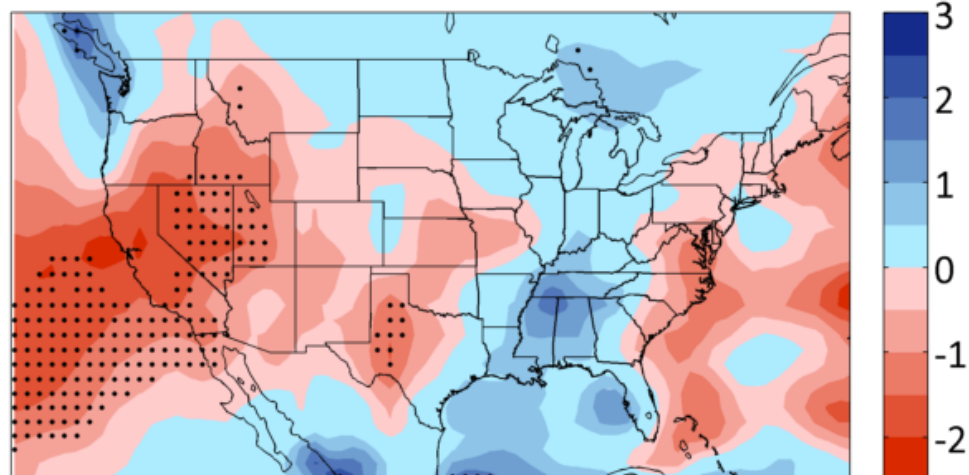


Results: new 21st-century projections (regional-mean weights)

"Intelligent" ensemble mean precipitation trend (cm/year)

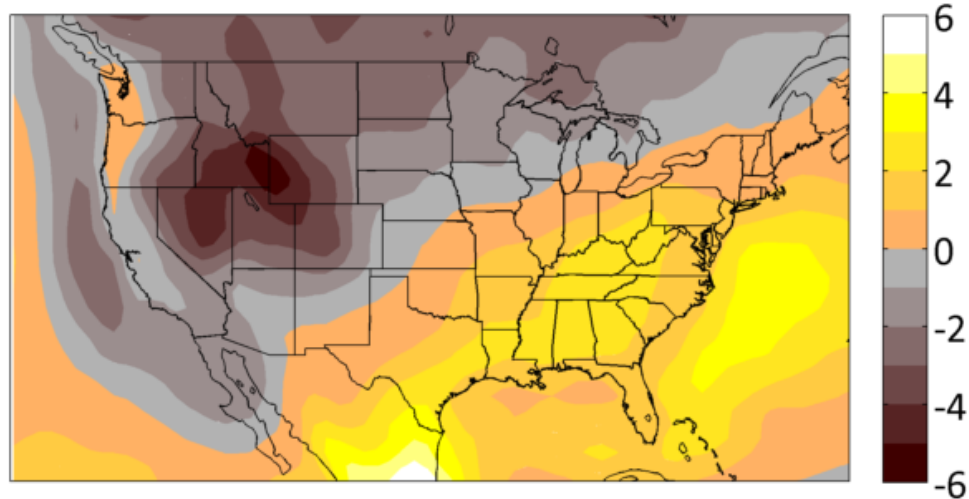


Difference between "Intelligent" and Equal-weight ensemble means (cm/year)

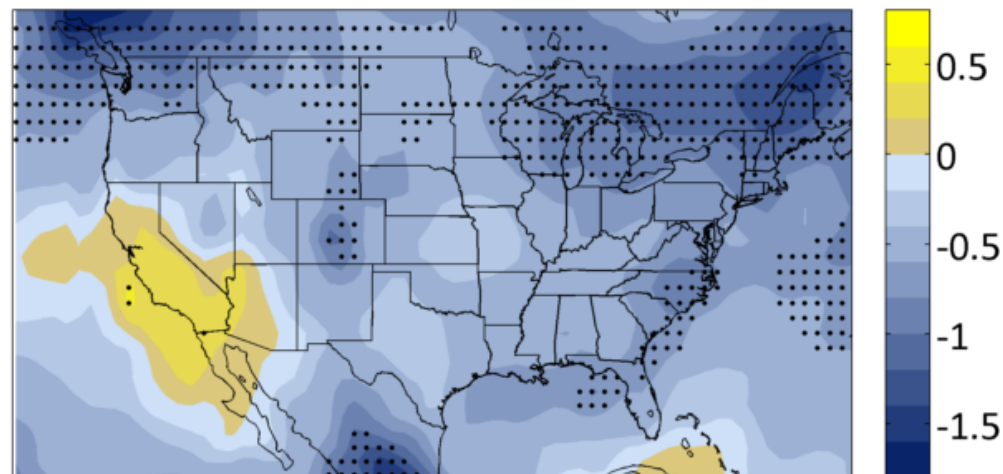


Results: new 21st-century projections (regional-mean weights)

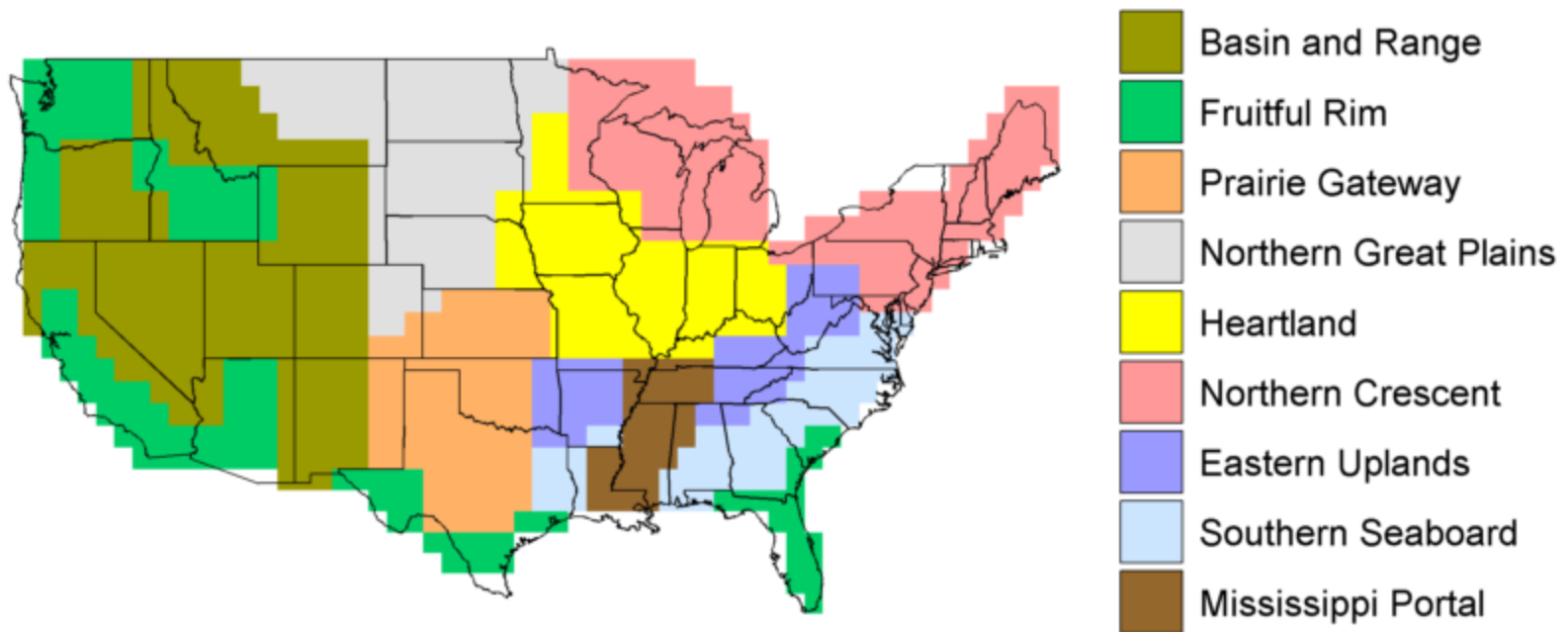
"Intelligent" ensemble mean surface shortwave radiation trend (W/m^2)



Difference between "Intelligent" and Equal-weight ensemble means (W/m^2)

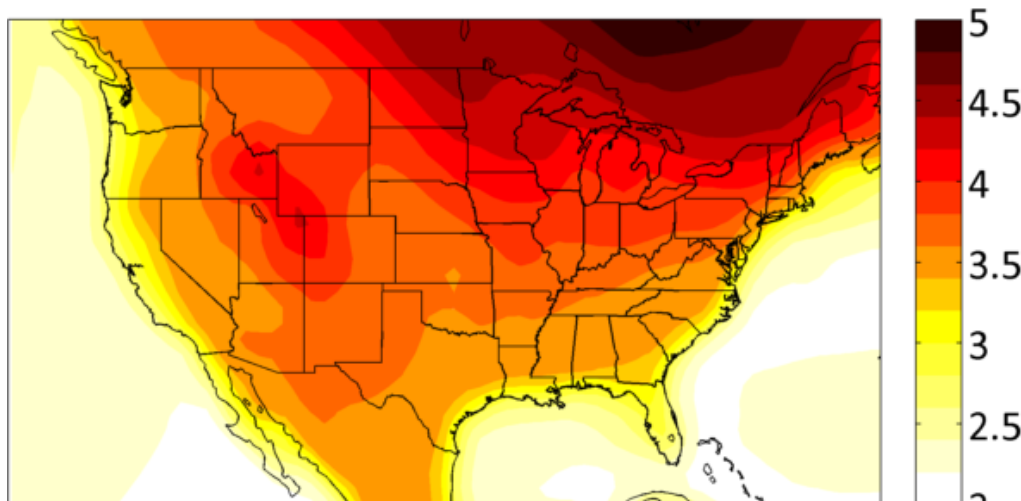


USDA Farm Resource Regions (1° resolution)

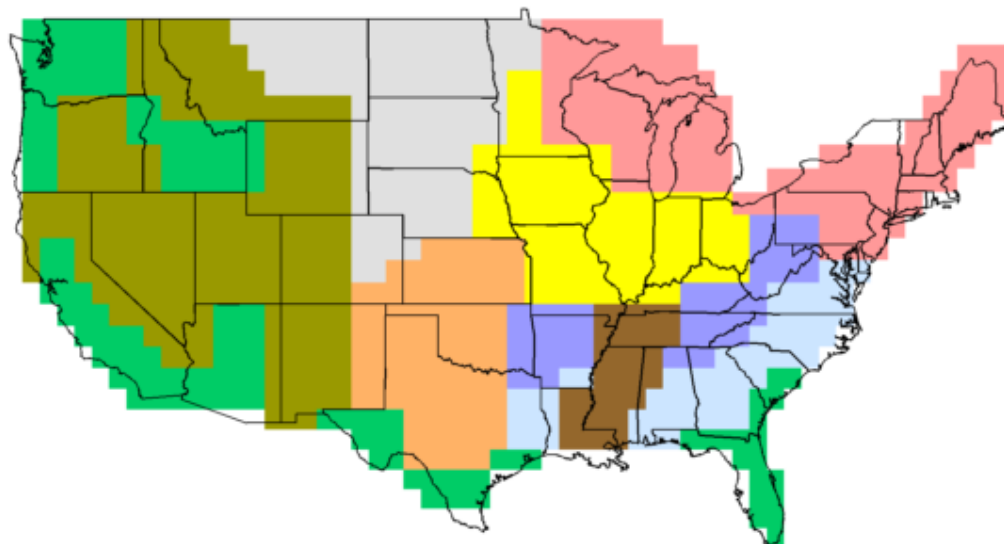


Results: new 21st-century projections

"Intelligent" ensemble mean temperature trend (°C)



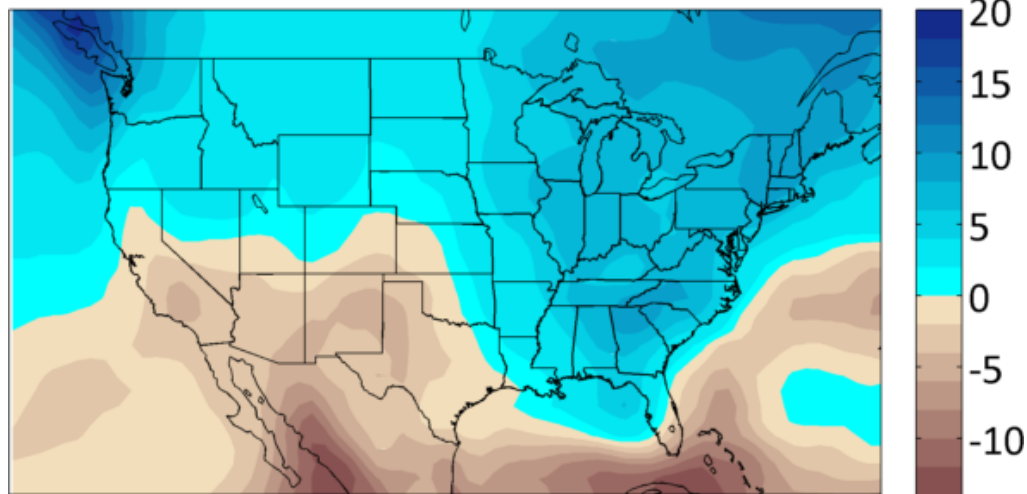
US mean temperature increase: 3.9 °C



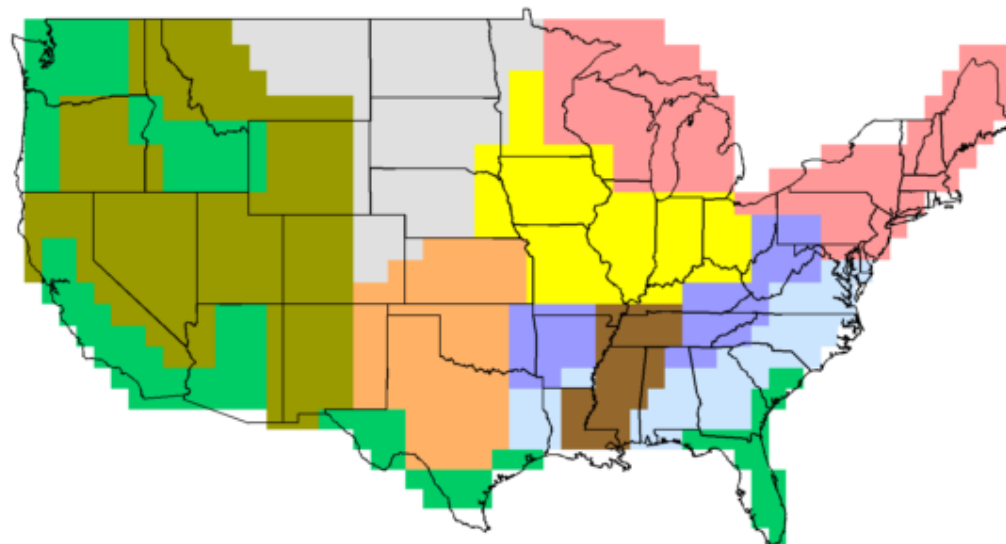
- Basin and Range: 3.9 °C
- Fruitful Rim: 3.4 °C
- Prairie Gateway: 3.8 °C
- Northern Great Plains: 4.1 °C
- Heartland: 4.1 °C
- Northern Crescent: 4.3 °C
- Eastern Uplands: 3.8 °C
- Southern Seaboard: 3.5 °C
- Mississippi Portal: 3.6 °C

Results: new 21st-century projections

"Intelligent" ensemble mean precipitation trend (cm/year)



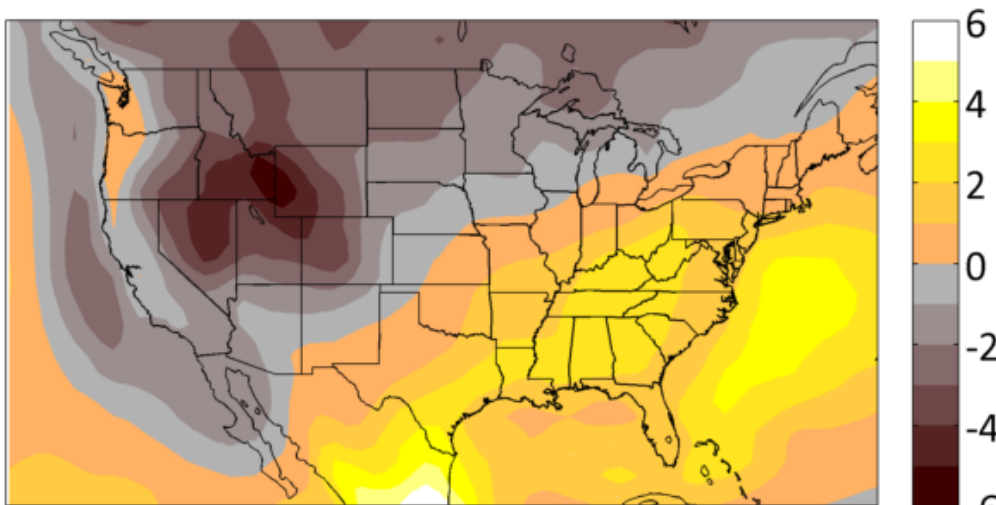
US mean precipitation increase: 3.4 cm/year



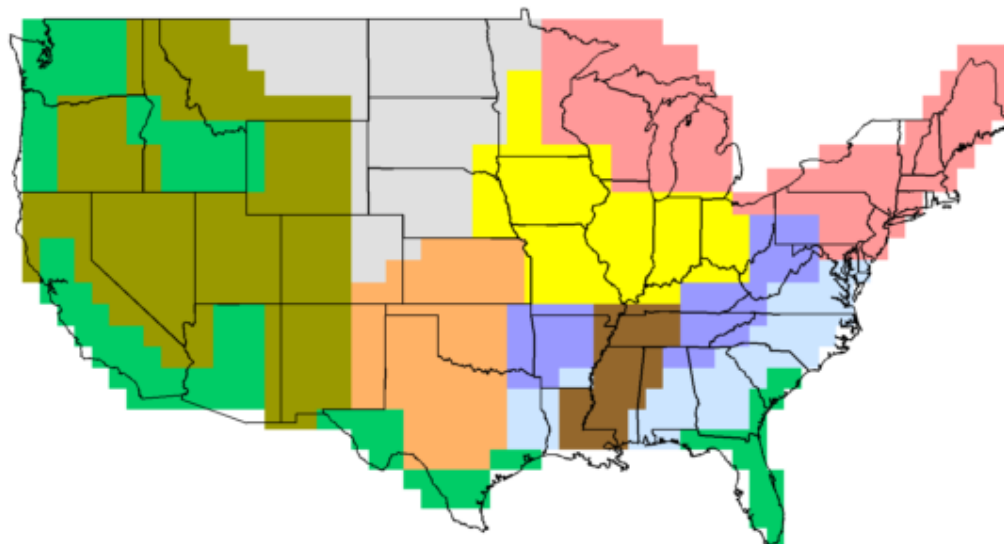
- Basin and Range: 0.6 cm/year
- Fruitful Rim: 0.8 cm/year
- Prairie Gateway: -1.8 cm/year
- Northern Great Plains: 2.7 cm/year
- Heartland: 7.2 cm/year
- Northern Crescent: 9.1 cm/year
- Eastern Uplands: 6.8 cm/year
- Southern Seaboard: 6.8 cm/year
- Mississippi Portal: 5.4 cm/year

Results: new 21st-century projections

"Intelligent" ensemble mean surface shortwave radiation trend (W/m^2)



US mean decrease in surface solar radiation: -0.33 Watts/m^2



- Basin and Range: -2.4 Watts/m^2
- Fruitful Rim: -0.5 Watts/m^2
- Prairie Gateway: 0.7 Watts/m^2
- Northern Great Plains: -1.9 Watts/m^2
- Heartland: 0.7 Watts/m^2
- Northern Crescent: -0.1 Watts/m^2
- Eastern Uplands: 2.7 Watts/m^2
- Southern Seaboard: 2.5 Watts/m^2
- Mississippi Portal: 2.6 Watts/m^2